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How to measure sedentary behavior at work?

Gil Boudet¹, Pierre Chausse², David Thivel^{3,4}, Sylvie Rousset⁵, Martial Mermillod^{4,6}, Julien S Baker⁷, Lenise M Parreira¹, Yolande Esquirol⁸, Martine Duclos⁹, Frédéric Dutheil^{10,11}

¹Université Clermont Auvergne, CNRS, LaPSCo, Physiological and Psychosocial Stress, University Hospital of Clermont–Ferrand, CHU Clermont–Ferrand, Preventive and Occupational Medicine, F–63000 Clermont–Ferrand, France

²Université Clermont Auvergne, CNRS, LaPSCo, CATECH (Cellule d’Accompagnement Technologique – Department of Technological Accompaniment), F–63000 Clermont–Ferrand, France

³Université Clermont Auvergne, Laboratory of the Metabolic Adaptations to Exercise under Physiological and Pathological Conditions (AME2P EA 3533), F–63000 Clermont–Ferrand, France

⁴Institut Universitaire de France, Paris, France

⁵Université Clermont Auvergne, INRA, UNH, Unité de Nutrition Humaine, F-63000 Clermont-Ferrand, France

⁶Université Grenoble-Alpes, CNRS, LPNC, Grenoble, France

⁷University of the West of Scotland, Institute of Clinical Exercise and Health Sciences, School of Science and Sport, Hamilton, Lanarkshire, ML3 0JB, Scotland, UK

⁸Université Toulouse 3, INSERM UMR-1027, Health Economics and Public Health, Department of Epidemiology, Toulouse-Rangueil University Hospital, Toulouse University School of Medicine, Occupational and Preventive Medicine, Toulouse, France

⁹Université Clermont Auvergne, INRA UMR-1019, University Hospital of Clermont–Ferrand, CHU Clermont–Ferrand, Sport Medicine and Functional Explorations, CRNH, F–63000 Clermont-Ferrand, France

¹⁰Université Clermont Auvergne, CNRS, LaPSCo, Physiological and Psychosocial Stress, University Hospital of Clermont–Ferrand, CHU Clermont–Ferrand, Preventive and Occupational Medicine, WittyFit, F–63000 Clermont–Ferrand, France

¹¹Australian Catholic University, Faculty of Health, School of Exercise Science, Melbourne, Victoria 3065 Australia

Address for correspondence: Australian Catholic University, School of Exercise Science, Faculty of Health, Melbourne, Victoria 3065, Australia; E-Mail: frederic.dutheil@acu.edu.au

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Abstract

Prolonged sedentary behavior (SB) is associated with increased risk for chronic conditions, and due to technological advances, the working population is in office settings with high occupational exposure to SB. There is a new focus in assessing, understanding and reducing SB in the work setting. So, measuring accurately SB at work is a new goal. There are many subjective (questionnaires) and objective methods (monitoring with wearable devices) on the place. Therefore, we aimed to provide a global understanding on methods currently available for SB assessment at work. Available questionnaires are the most accessible method for a large population with a limited budget. SB at work (time sitting) is accessible from some specific items and it is also possible to deduct SB in measuring PA at work that is easier measurable. For a restrictive group, SB at work can be objectively measure with wearable devices (accelerometers, heart-rate monitors, pressure meters, goniometers, electromyography meters, gas-meters) and can be associate with a subjective measure (questionnaire). Number of devices wears increase the accuracy but make the analysis complex and time consuming.

Keywords: Occupational Health, Sedentary lifestyle, Workplace, Sedentary behaviour measurement, Work, Questionnaires, Wearable devices, Recommendations

Introduction

Sedentary behaviour (SB), defined as sitting or lying with low energy expenditure ≤ 1.5 METs [1] is an independent risk factor for a number of adverse health outcomes. People in modern industrialized societies spend more and more time engaged in SB during the main domains of living, like working (e.g. using computers), travelling (e.g. driving a car) and during leisure (e.g. watching television) [2; 3]. Further, a greater proportion of the workforce is now employed in low activity occupations such as office work. Office workers were found to be sedentary for 76% of their working day [4]. Prospective studies have demonstrated a positive association between self-reported times spent sitting and chronic disease and all-cause mortality [5; 6; 7; 8; 9; 10; 11; 12; 13]. There is a dose response relationship between self-reported daily total sitting and all-cause mortality, with a 2% increase in all-cause mortality per hour spent sitting per day [14] even after adjusting for the extent of moderate or vigorous physical activity [15; 16]. This indicates that much time spent seated infers a risk for health impairments irrespective of the level of physical activity. SB can be measured by declarative methods (auto-administrate questionnaires) and objective methods (observation, video or technical instruments). Descriptive parameters of physical activity and sedentary activity most used are duration, frequency, intensity, domain or context (leisure, work, domestic, transport) and the type of activity. Indicators combining these parameters can be calculated globally or for each one of the domains. The most common are the volume (time x frequency) and the energy expenditure (duration x frequency x intensity), the latter being rather calculated to account for overall physical activity. Time spent in front of a screen (television, video, video games, computer ...) is currently the most used sedentary indicator and in the majority studies, it is the time spent watching television that is measured by survey. Considering the public health impact of SB at work, there is now a growing research burden around sedentariness at work. However, SB is

measured through a wide range of methods, but no scientific articles provide a global overview on all methods to measure sedentariness.

Objective

The aim of this synthesis was to provide a global understanding on methods currently available for SB assessment at work.

Characteristics of sedentary behaviour

Daily duration of SB is the metric normally used for considering health effects of SB. The time patterns of SB can also be important for evaluating its health consequences. For example, time spent in continuous prolonged bouts of SB may be more detrimental to health than the same duration spent in shorter bouts [17; 18]. Investigations of SB at work should not only address duration of SB, but even the durations of SB periods, as well as the periods of non-SB. The context of SB is also important (what, where, why, when and with whom).

Methods of measuring sedentary behaviour

Declarative methods - Self-reported questionnaires

These questionnaires are the most common method SB and rely on participants' recall ability[19]. The commonly used self-report questionnaires for SB at work assessment are: Global Physical Activity Questionnaire (GPAQ), International Physical Activity Questionnaire (IPAQ)[20; 21], Workfoce Sitting Questionnaire (WSQ, Adapted from Marshall Questionnaire), Occupational Sitting and Physical Activity Questionnaire (OSPAQ)[22] and European Physical activity Questionnaire (EPAQ) [23]. Questionnaires vary by what they

measure (e.g., mode, duration, or frequency of PA and SB), how data are reported (e.g., activity scores, time, calories), by the time of recall (e.g., last week or over the 12 last months), quality of the data (e.g., measures of intensity, differentiating between habitual and merely recent activities, inclusion of leisure and non-leisure activity), and how data are obtained (e.g., paper and pencil assessment, computerized questionnaire, interview) [24]. The strength of questionnaires is their low cost and low burden of effort, both for the participant and for the researcher. Thus, it is feasible to use questionnaires to collect information from large populations. However, self-reported sedentary time at work has been shown to be both biased and imprecise, less robust in measuring light or moderate activity, assessing energy expenditure, and may be limited by the dependency on written language (i.e., questions), and external factors (i.e., social desirability, complexity of the questionnaire, age, and seasonal variation) [25; 26; 27; 28], and is therefore generally regarded to have severe limitations when used in studies of occupational SB [29]. Characteristics and performances of questionnaires for SB assessment at work are presented in Table 1.

Objective methods

Visual observation (direct or videotaped)

Visual observation, either on-site or videotaped is another method for assessing SB at work. Observational methods are still a common approach among researchers and practitioners for assessing body postures at work [29]. This method of assessment is often use by ergonomists and when activity is restricted to a delineated space (e.g., work space). This flexible method is valuable in gathering contextual information (e.g., preferred location, time, and clothing) and details of the SB (e.g., type, personalized variations to activities). However, observations are generally time consuming and expensive per unit of working time observed [30], and they are

therefore only feasible with relatively short assessment periods and limited population sizes. Observation-based methods are also associated with considerable uncertainty due to observers differing in ratings [31]. Visual observations at the workplace can also be challenging due to the logistic burden associated with data collection and ethical aspects (e.g. observing work with patients). Observations may also modify the behavior of the observed worker (observational bias). Videotaped monitoring at work need also the authorization of employers and workers.

Cardiorespiratory assessment

Indirect Calorimetry (IC)

With IC total energy expenditure (TEE) is calculated from Weir's equation, taking oxygen consumption and carbon dioxide production into account [32]. This method has the potential to be used for accurate non-invasive routines but it involves costly medical material, and is not feasible in the context of epidemiological studies nor in free-living conditions. Thus this method needs to wear a facemask connected to a central unit that analyzed either the O₂ or both the O₂ and CO₂ concentrations during a scenario of controlled activities. The facemask was linked to the central unit worn in a backpack. The central unit analyzed the O₂ and CO₂ consumption in real time necessary for the TEE calculation. Thus by discriminating energy expenditure, SB is defined as seated, reclining or lying activities requiring low levels of energy expenditure (i.e., ≤ 1.5 METs), light-intensity physical activity (LPA) as standing is between 1.6–2.9 METs and Moderate- to vigorous-intensity physical activity (MVPA) require energy expenditure ≥ 3.0 METs). IC can evaluate sedentary time. These analyzers have become portable like the Cosmed K5 [33] or Metamax Cortex [34]. Their use over a long period can be difficult to support depending on the activity of the worker but feasible. Because of the relatively small absolute difference in energy expenditure between sitting and standing posture [35; 36], assessment of

energy expenditure only does not provide reliable information about the gross body posture. Therefore, assessing SB at work also requires measurement of body posture. Conversely, wearable devices may be used to assess a multitude of body positions at work, as per their anatomical location.

ECG-Holter

There is a linear relationship between cardiorespiratory stress and energy expenditure, and thus with activity intensity [37]. Heart rate (HR) can therefore be used to estimate energy expenditure, which complements the data of accelerometers, leading to an increased accuracy for assessing physical activity and SB [29; 38]. Different principles are available for assessing HR, with electrical (electrocardiography, ECG) and optical (photoplethysmography, PPG; blood volume pulse, BVP) sensor technologies being the most commonly used [39]. Electrical HR sensors detect the electrical signals which lead to contraction of the heart. The signal allows detection of each individual heartbeat, and thus a calculation of the HR. A 12-lead ECG is considered the gold-standard for non-invasive electrocardiographic assessment in clinical settings, while a portable 3-lead ECG-Holter system can be applied in the field. It allows abnormal heart rhythms and cardiac symptoms detection. ECG-Holter is a medical device (3 or 5 leads) and is for scientific research and medical domains. ECG-Holter commercially available consumer wearables are often based on 1-lead or 2-lead ECG setups (no medical device?). Although the validity and accuracy of the assessments are high, the technique is susceptible to artifacts from physiologic (emotion, stress, body temperature) or non-physiological factors like muscle activity, motion or poor contact between electrodes and the skin [40; 41]. Additional markers for subject-activated events and time correlates are included to allow greater diagnostic accuracy. Data are stored in the device using digital storage media (SD cards) and analyzed using software with technologist and physician editing and reporting.

Heart-Rate Monitors

There are two different types of technology used by HR monitors: the electrical signal detection “ECG-based” (RR interval) and optical sensor. ECG-based sensors work by detecting electrical signals sent through the heart each time it contracts. Optical HR sensors use integrated photodiodes which shine light onto the skin and captures the amount of reflected light. The amount of reflected light will change over time, following the changes in the volume of the blood vessels, and this can be used to assess the HR [42]. These sensors can, in principle, be applied anywhere on the skin, allowing for great flexibility, and they are also cheap. Typical placements are at the wrist, the ear lobes or the fingertips. The main limitation of this technique is its sensitivity to movement artifacts [43] and skin texture. ECG chest straps (heart belt) still offer the most reliable, consistent and accurate way to monitor HR thanks to higher sampling rates and the position closer to your heart [44]. However, many people prefer the comfort and convenience of optical sensors built into watches (Applewatch). HR monitors capture EE during working activities not involving vertical trunk displacement that many accelerometers and pedometers miss [45] and are best suited to categorize subjects’ PA levels (i.e., highly active, somewhat active, sedentary) as opposed to the exact amount of PA. These devices tend to show discrepancies particularly at very high and low intensities [46]. Discrepancies are due to HR and energy expenditure not sharing a linear relationship at rest and low-intensity (as the PA is confounded by unrelated factors such as caffeine, stress, body position) or high intensity PA [46]. Age, body composition, muscle mass, gender, and fitness level also affect this linear relationship or reduce its accuracy [47].

Accelerometers

Accelerometers are currently used to measure PA intensity category and SB and have become the method of choice for measuring SB given their accuracy, ability to capture large amounts of data, and ease of administration, particularly in large studies. These devices measure acceleration (counts) in real time and detect movement in up to three orthogonal planes (anteroposterior, mediolateral, and vertical) [48]. The accelerometers assume that force produced by the body (muscles) is proportional to the acceleration detected, and therefore related to EE. These devices tend to measure sedentary time in two different ways. Posture sensors measure sedentary time either through an accelerometer in conjunction with gravitational components and proprietary algorithms or through the alignment of the area of the body surrounding the pelvic area (ie, pelvic alignment is different depending on standing, sitting, and lying). Some accelerometers are unable to differentiate body position (i.e., sitting, lying, standing) or walking intensity [49]. New accelerometers demonstrate better validity, compared to DLW, than older models. However accelerometers induce a reactivity bias [50], and do not provide any contextual information (i.e., setting and type of activity). Notably, the relationship between accelerometer activity counts and energy expenditure depends on the count cut-point applied to the data; choosing different cut-points can differentially influence measurements of physical activity intensity [51]. Most of the time, the acceleration results to characterize sedentary (absence of movement) and active behaviours. The most commonly used cut-points for adult populations are < 100 counts/minute for SB, 100–1,951 counts/min for light-intensity PA (LPA), and $\geq 1,952$ counts/min for moderate- to vigorous-intensity PA (MVPA) for the ActiGraph accelerometer [52; 53]. However, these cut-points were developed in specific populations and during strict, laboratory-based protocols. Other studies validating the ActiGraph have found vastly different cut-points for SB (range 50–250 counts/min) and MVPA (191–2,691 counts/min) in adults, depending on the population and type of validation

setting [54; 55]. The cut-point method has several limitations; it cannot differentiate standing from sitting/lying, but standing is considered LPA because it elicits different physiologic responses and has different long-term health consequences than sitting/lying [56; 57]. Thus, the interpretation of what is considered to be active behaviour is consequently different and makes the comparison between the studies difficult. Obese people spent more time in sedentary behaviours than normal weight individuals [58; 59]. Thus cut-points have to be more accurate to show difference among normal-weight and obese populations. An accelerometer worn on the right thigh, achieved high accuracy for classification of three distinct PA intensity categories (SB, LPA, and MVPA) as well as breaks in SB in a semi-structured setting. An accelerometer worn on the left wrist also had high accuracy for assessment of SB but had some misclassification of LPA and MVPA, whereas accelerometers worn on the right wrist and hip had the lowest accuracy for assessment of all PA intensity categories and for measuring breaks in SB. These findings support the use of a thigh-worn accelerometer for assessment of time spent in different PA intensity categories. Alternately, for researchers using wrist-worn accelerometers to assess PA, wear on the non-dominant wrist is likely to allow for higher measurement accuracy than wear on the dominant wrist [60]. Due to limitations of the cut-point approach to measuring PA intensity categories, researchers have utilized machine learning models to improve accuracy of PA measurement worn on various body locations [61; 62]. An accelerometer does not give the position information of the subject. It will be completed by a gyroscope (measuring orientation and angular velocity) (Samsung Gear S3) and a magnetometer (detecting Earth's magnetic three perpendicular axes X, Y, Z) (Actigraph GT9X) [63]. A GPS, can complete this arsenal of sensors and will give the geographical position and speed but outside only. Some devices include a brightness sensor to assess sleep quality. These wearable lightweight devices are easily forgotten by users. The researcher should take care to check the sampling frequency, resolution and the maximum amplitude of the device. These three

parameters are generally correlated to the price of the wearable monitor. In order to make long observation, it is also necessary to check the device battery and storage space. Recent smartphones or smartwatches are equipped with all the mentioned sensors.

Smartwatches and smartphones

Smartwatches are computerized devices or small computers intended to be worn on the wrist, and have expanded functionality that is often related to communication. Most current smartwatch models are based on a mobile operating system. Manufacturers continue to develop their products and add features, such as waterproof frames, global positioning system (GPS) navigation systems, and fitness/health tracking features [16]. With the addition of reliable, sensitive inertial sensors on them, smartwatches can now be used to capture and analyze hand gestures, such as smoking or other activities [17]. In a recent meta-analysis [64] the most popular smartwatches (connected devices) on the market were compared : from Fitbit, Garmin, Apple, Misfit, Samsung Gear, TomTom, and Lumo. Overall, wearable devices tend to underestimate energy expenditure compared to criterion laboratory measures (Oxycon Mobile, CosMed K4b2, or MetaMax 3B). Additionally, while wearable technology devices are better at estimating energy expenditure during moderate to vigorous activities, getting better as the intensity increases, validity becomes poorer with low intensity and sedentary. All wrist and forearm devices had a tendency to underestimate HR, and this error was generally greater at higher exercise intensities and those that included greater arm movement. HR measurement was also typically better at rest and while exercising on a cycle ergometer compared to exercise on a treadmill or elliptical machine. Step count was underestimated at slower walking speeds and in free-living conditions, but improved accuracy at faster speeds. Since smartphones are basically mobile computers and are widespread among the general population, they offer a convenient alternative to smartwatches or other wearable devices. Today, a middle-range

smartphone assembles a lot of sensors for example an Asus Zenfone 4 (<https://www.asus.com/uk/Phone/ZenFone-4-ZE554KL/Tech-Specs/>) have an accelerator, an e-compass, a gyroscope, a proximity sensor, an ambient light sensor, GPS (Global Position System) or GLONASS (Global Navigation Satellite System)... It is also possible to add an HR belt or a watch and now a gas analysers. Smartphones are particularly attractive for context awareness and phone-based personal information [65]. Activity recognition rates is phone-position-dependent. To measure the periodicity of body movement different fixed positions have been tested: hand, pants pocket, shirt pocket and handbag [66]. Some fixed smartphone positions are a major disadvantage in free-living conditions. The method of calculation used would quickly consume not only the battery power but the mobile CPU as well when applied for long recording periods (12 h). Long-term smartphone monitoring is wireless and require periodic power supply. Another point consist to choose the accurate available application.

Mobile applications

Smartphone applications have received a considerable amount of attention in medical science. In 2016, the Play Store displayed 105,000 and the Apple Store 126,000 mHealth-related apps in health and fitness and medical categories (Research2guidance, 2018; [67]). These applications propose physical exercises and fitness programs with or without connected objects such as wristband, pedometer, scale, HR monitor, smartphone and smartwatch. When the mobile applications integrate the use of sensors (accelerometer, HR monitor, GPS), they inform the user of steps, distance, energy expenditure, speed and heart frequency. The three most popular applications are Fitbit, Noom, and AppleHealth (Table 2). These special features are welcomed by the users. Conversely, most of the applications are not scientifically validated. Two applications, were recently scientifically validated to assess accurately time spent in SB, light-, moderate- and vigorous -intensity and the TEE associated: WellBeNet (eMouve) and

IntellilifePro. These two applications were specially developed to discriminate SB from light intensity activities such as standing or slow walking. Accelerometry data are collected via smartphones (WellBeNet (eMouve)) or via both a smartphone and smartwatch (IntellilifePro).

E-Move

E-move (Android) application detects leg movements as the smartphone is worn in a front pants pocket. Different algorithms were designed for normal and overweight/obese adults. The TEE and time spent in the different activity categories given by the E-Mouve algorithms were compared with reference method or device: either Armband or indirect calorimetry (FitmatePro, Cosmed). Absolute error of the TEE and activity estimates are 5.6% and 5.0%, respectively in normal weight volunteers, and 8.6% and 5.0% in overweight/obese participants [68; 69].

IntellilifePro

IntellilifePro, **using both a smartwatch and a smartphone** (Android or Apple) detects both leg and wrist movements. A such approach based on the use of two connected objects (smartphone and smartwatch) can discriminate passive from active sitting when in a sitting posture, the arm, the wrist and/or the hand are engaged in the movement. Absolute error of the TEE and activity estimates are 5% in free living conditions and 3.1%, 2.8%, 1.5% and 0.04%, respectively for the time spent in SB, light-, moderate- and vigorous -intensity were The absolute mean gap of total energy expenditure was lower than 5% in free living conditions. (Duclos et al., 2016).

Pressure sensors

The other way technologies tend to measure sedentary time is via pressure sensors. These pressure sensors are either located in a sock, shoe, or chair. When placed in a sock or shoe, the pressure can determine standing when there is pressure on the sensor and when there is less pressure the wearer is sitting or lying. Located on a chair, there is a simple binary outcome:

when the pressure sensor is active the user is sitting and when it is inactive there is no sitting behaviour at that site.

Table 2. Decision support for choosing the best suited wearable for a particular study on SB, depending on several factors, including accuracy, duration of measurements, and available budgets

Limitations

Smarts Clothing (shirts, socks, yoga pants, shoes, bow ties with secret cameras, helmets, and caps with a wide range of sensors and features), goniometers (measure an angle and angular position), electromyography meters (measure the electrical activities of muscles EMG) and wearable Camera are voluntarily excluded of the presented devices because not reasonably applicable at work (for a variety of reasons).

Conclusion

The wide range of available wearables monitors with different characteristics offers a variety of opportunities to assess SB at work. The main factors of work (inside or outside, working movements and postures) and study population (i.e., number, age, gender, body weight, co-morbid conditions) may also impact choosing a kind of device. Four key features of a SB measure should be considered when choosing one for a research study: (1) quality of SB measured (e.g. time spend or EE), (2) objectivity of the data, subject burden (e.g. time and/or effort required to complete), (3) cost/burden to administer, and (4) specific limitations, discussed above. Available questionnaires are the most accessible method for a large population with a limited budget. SB at work (time sitting) is accessible from some specific items. It is also possible to deduct SB in measuring PA at work that is easier measurable. Valid and reliable assessments of SB require measurements of both energy expenditure and body posture (dual or

multiple wearable devices with sensors). Accurate measure of SB at work need a sufficient number of subjects affected to the same assigned task and an objective measure coupled to a questionnaire (mixed approach method). For a restrictive group, SB at work can be objectively measure with wearable devices (accelerometers, heart-rate monitors, pressure meters, goniometers, electromyography meters, gas-meters) and can be associate with a subjective measure (questionnaire). Number of devices wears increase the accuracy but make the analysis complex and time consuming.

Furthers studies are necessary to improve strengths and weakness of subjective or objective methods to assess SB at work.

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Author Contributions Statement

Conflicts of interest

Here, the authors declare that the submitted work was carried out in the absence of any personal, professional or financial relationships that could potentially be construed as a conflict of interest.

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Table 1. Characteristics of self-report questionnaires to measure SB at work

Not finalized

Measure of Interest	Period(s)	Categories of Activity Included	Input	Output	Special Notes
GPAQ	Typical week	Activity at work, Travel to and from places, Leisure-time	MET-min per week.	PA: min/week in MVPA, Sitting: hours/week). PA at work: MET-minutes/week. physical activity MET-minutes/week.	Designed for adults of both sex. For face-to-face interviews conducted by trained interviewers. Total 16 items in three domains. 20 minutes. Many domains explored. Quantifies exposure. Cross cultural application.
WSQ	Past week	Total domain-specific sitting based on work and non-workdays in adults	Duration (min per week)	Time spend sitting at work and non-workdays	Acceptable measurement properties for measuring sitting time at work on a work-day and for assessing total sitting time based on work and non-workdays.
OSPAQ	Past five working days	Work time spent sitting, standing, walking, and doing heavy labour, as well as the total length of time worked in the past five working days	Duration (min per week)	Time spend sitting, standing and walking, doing heavy labor and total length of working	Acceptable reliability and validity measurement properties in the office workplace setting
EPAQ	Typical week	Sitting and standing, moderate PA inleisure and working time, heavy labor at work	Duration (min per week)	Time spend standing, sitting, doing moderate PA in leisure and working time, heavy labor at work	Do not distinguish moderate and vigorous PA, but focus on at list moderate PA. Assessed walking and bicycle separately, Shorter than GPAQ and IPAQ

MET = Metabolic equivalent of task (1 MET represents 3.5 ml/kg/min oxygen consumption)
 Questionnaires: GPAQ Global activity Questionnaire, IPAQ International Activity questionnaire, IPAQ-S (Short Version), IPAQ-L (Long Version), WSQ, OSPAQ, EPAQ

Table 2. Characteristics and physical activity parameters evaluated by the three most downloaded mobile applications

Application	Operating system	Wearable monitor	Measured parameters
Fitbit	Android iOS Web	Accelerometer (wristband) Manual input	Number of steps or stairs Intensity Distance Calories burnt
Noom	Android iOS	Smartphone sensors GPS HR monitor	Distance Calories burnt Speed
Apple Health	iOS	RunKeeper (GPS) Moves (GPS and smartphone sensors) Manual input	Distance Calories burnt Number of steps Duration of activities

Table 3. Instrument, raw unit, cost and environment

Instrument	Measure/raw unit	Cost	Environment
Survey questionnaire	Response quote qualitative	Depend of the support paper, smartphone, application	Possible at work but take time
Accelerometer	g or count (on X,Y,Z axis 3D, position, direction, brightness illuminance lux)	300€/unit	Easy to wear even at work
Heart rate monitor, ECG-Holter	RR interval, Beat/minute	25€to 1000€	Easy to wear even at work
Gas analyser	O2 CO2 consumption/production (liter, m3...)	25k€	Easy to wear but not for a long time especially at work
Video observation	Video qualitative	50€to--	Possible be careful with authorization
Smartphone	All sensors (XYZ g, m/s, position, direction, brightness illuminance lux ...)	Smartphone 300€but depends of the application cost	Easy to wear

Figures' Legend

Figure 1. Flowchart of decision strategy for the selection of wearable devices

Figure 2. Attachment on the body of wearable devices

Figure 2. Categorization of wearable devices and the accuracy and complexity of data assessed and provided

Figure 1. Attachment on the body of wearable devices

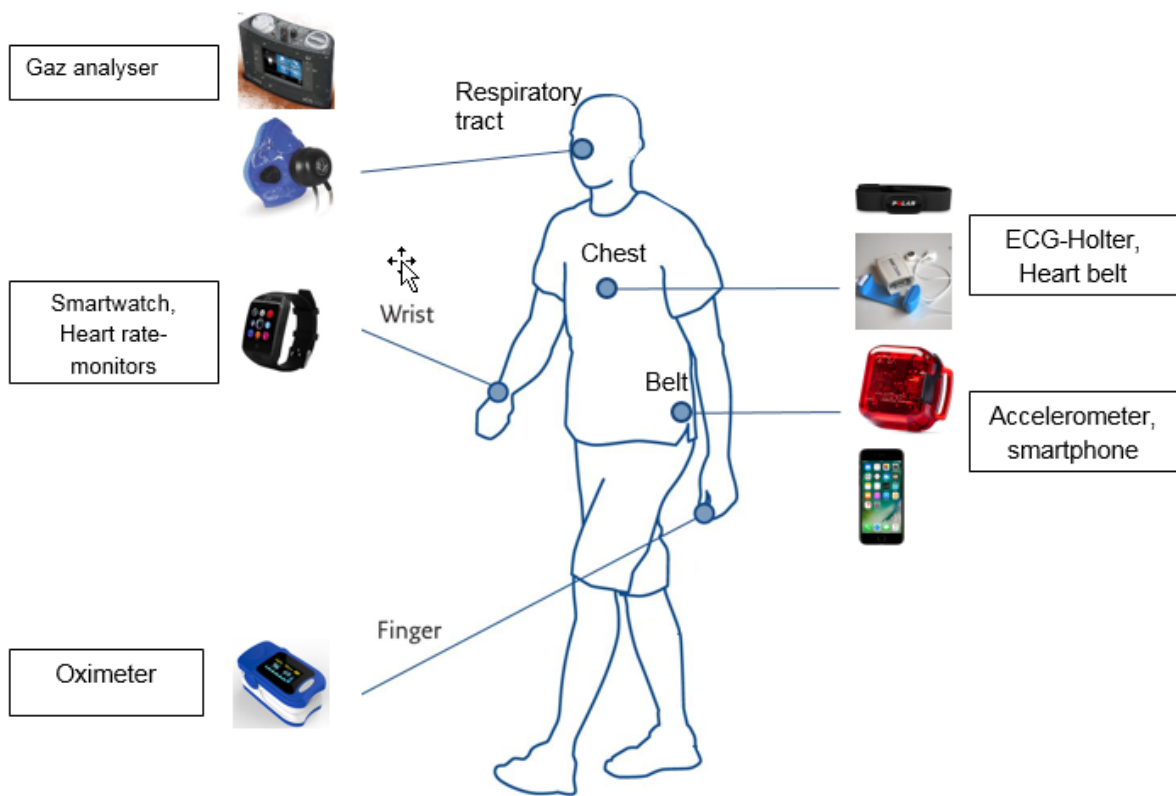


Figure 2. Categorization of wearable devices and the accuracy and complexity of data assessed and provided

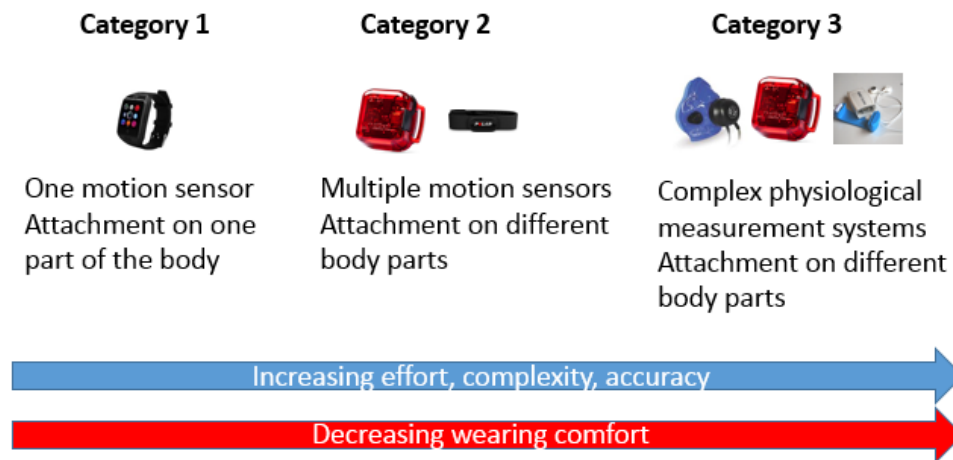


Figure 3. Flowchart of decision strategy for the selection of wearable devices

